

# On the importance and feasibility of forecasting data in sensors

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## Abstract

The first generation of wireless sensor nodes have constrained energy resources and computational power, which discourages applications to process any task other than measuring and transmitting towards a central server. However, nowadays, sensor networks tend to be incorporated into the Internet of Things and the hardware evolution may change the old strategy of avoiding data computation in the sensor nodes. In this paper, we show the importance of reducing the number of transmissions in sensor networks and present the use of forecasting methods as a way of doing it. Experiments using real sensor data show that state-of-the-art forecasting methods can be successfully implemented in the sensor nodes to keep the quality of their measurements and reduce up to 30% of their transmissions, lowering the channel utilization. We conclude that there is an old paradigm that is no longer the most beneficial, which is the strategy of always transmitting a measurement when it differs by more than a threshold from the last one transmitted. Adopting more complex forecasting methods in the sensor nodes is the alternative to significantly reduce the number of transmissions without compromising the quality of their measurements, and therefore support the exponential growth of the Internet of Things.

## I. INTRODUCTION

Big Data analytics are beginning to be applied as part of the process of the sensor nodes analysis and management, for example, to increase the number of measurements when the environment is changing. The efficiency of such data analytic methods is highly correlated with the quality of the data used, i.e., reported by the sensors [5]. Among other aspects, the

information quality depends on the temporal relevance, the data resolution and the chronology of the data [6].

At the same time, sensor nodes have evolved in the last years from devices with constrained energy and memory resources [1], to the point where some modern hardware can harvest energy and work autonomously for longer periods [2]. According to [?], the most recent technologies of wireless power charging should allow the energy constraint of the sensor nodes to be overcome in the future. Moreover, besides the hardware evolution, the incorporation of Wireless Sensor Networks (WSNs) into the Internet of Things (IoT) [3] accelerates the evolution of the sensor networks, since smartphones and household appliances can easily become sensor nodes, by generating measurements and communicating them to their neighbors.

Although the hardware limitations tend to disappear, the medium access has been named as one of the key challenges in the next generations of wireless networks due to the increase on the number of wireless devices and traffic profiles [4]. Hence, the access to the data produced by neighboring wireless sensor nodes might remain an issue in the next generation of sensor networks. Also due to the limited channel resources, sensor nodes are usually programmed to transmit their measurements as rarely as possible. For example, the most intuitive solution is to transmit the measurements only when they differ by more than a certain threshold from the last value observed, i.e., when the data probably contains new—and valuable—information.

Driven by the sensor nodes' evolution, there are several approaches to reduce the number of transmissions by adopting complex forecasting methods. They substitute the simpler strategy of avoiding a transmission if the current measurement is the same—or very similar—to the last one transmitted [7], [8], [9], [10]. As detailed in our previous work [11], theoretically, high accuracy forecasts can reduce the amount of transmissions by around 30% in an ordinary scenario and by up to 85% in sporadic cases.

Meanwhile, there are no comparison studies that show whether such a high accuracy can be achieved in practice or not. In this work, we show the potential benefits of adopting forecasting methods in different scenarios through experiments using real sensor data. To do that, we first illustrate the importance of analyzing the effectiveness of the forecasts when applied to real use cases, i.e., based on the numerical measures of forecast accuracy, we adopt a strategy to evaluate the practical benefits of the forecasting methods to sensor networks that can be adopted as a reference in similar scenarios. For instance, considering that the sensors' resolution is the

smallest interval that can be reliably measured, their resolution is the highest measurement quality that a sensor network can provide and the smallest error accepted in the forecasts. Finally, our main contribution is a broad study about how much sensor networks can benefit by forecasting measurements in the sensor nodes to diminish their number of transmissions without reducing the quality of their measurements.

Our results reinforce the idea that it is possible to shift part of the data computation to the sensor nodes, reducing the number of transmissions and the channel utilization. For the future on the Internet of Things, this work represents a step towards a distributed solution that can help to detain the significant increase in the number of transmissions and consequential quality reduction.

In Section II, we clarify which kind of application we expect the sensor networks to be used for and describe the datasets that will be evaluated further. After that, we explain what forecasts are and their difference to ordinary predictions, as well as introduce the terms and methods currently adopted in data science applications in Section III, before detailing how important their use is in sensor networks in Section IV, and describing the related work in Section V. Then, using real data collected in other studies, we synthesize the evolution of the sensor nodes based on their memory and computing capabilities, and observe how it can impact the results obtained by the state-of-the-art forecasting methods that are broadly used in other applications. Based on the accuracy of the results shown in Section VI, we study their effectiveness in sensor network applications in Section VII. Finally, we draw conclusions about their adoption according to the trade-off between their computational complexity and their potential accuracy in Section VIII.

## II. SENSOR NETWORK APPLICATIONS

We use the term sensor network to denote any set of sensor nodes that can measure environmental parameters and report them (through their neighbors, if necessary) to a gateway (GW) that works as a central server, collecting and storing all the data. Such networks, however, may have different applications, measure different data types and be influenced by contrasting environmental circumstances. In order to categorize their characteristics and requirements, we classify sensor network applications into two broad classes according to their nature: monitoring and tracking.

As defined in [12], monitoring applications comprise mainly “indoor and outdoor environmental monitoring, health and wellness monitoring, power monitoring, inventory location monitoring, factory and process automation, and seismic and structural monitoring”. Hence, in such applications, it is more common to encounter temperature, relative humidity, light, solar radiation, wind speed and soil moisture sensors, among others, that can measure environmental parameters; and the data types are usually periodic, i.e., each type follows a similar pattern through the days (or weeks) that could be used, for example, to change their sampling rate at a certain time of the day, if the sensor nodes had enough computational power to store enough data and compute such a decision.

On the other hand, tracking applications include especially human tracking, battlefield observation (e.g., enemy tracking), animal tracking and car tracking in smart cities. This kind of application usually requires more powerful sensors, such as cameras, microphones and radio-frequency identification, and is less tolerant to delays and single point of failures. In many target tracking applications, the data is sensed by only one sensor node at a time, differently from monitoring applications that use several sensors to measure the environmental parameters. As a result, the computation in the sensor nodes is heavier, because they tend to oversample the data and avoid missing variations that will eventually happen. Moreover, the data is usually processed and only the relevant information is transmitted to the GWs [13].

Both application types have in common the data heterogeneity in terms of scales, since their values may be stored as nominals, ordinals, intervals or ratios [14]. Moreover, different datasets may use different units of measurement, for example, distances could be represented in kilometers or miles, temperatures could be represented in Kelvin, Fahrenheit or Celsius, and time intervals might be represented in seconds, minutes, hours or days. In conclusion, the difference between sensor measurements does not stem only from the origin of the data, but also from its representation.

We highlight a special use of sensor networks that may be incorporated in both application types: the event detection. Events can be detected by the GW after analyzing the data collected by the sensors, or by the sensor nodes, if they compute the data locally. The detection of an event is tightly tied to the scenario where it is applied and requires deep domain knowledge, including its causes and consequences. Missing or wrongly reporting an event (i.e., false negatives and false positives) have inherent costs that impact the operation of the system. Given that our goal

is to find a solution that would satisfy as many applications as possible, we do not focus on the act of detecting an event, because it would imply on assessing different (higher) costs generated by false positives and false negatives. We aim our attention at the data collection for general purposes, presuming that it can be adopted in a sensor network that detects events, if needed.

To represent monitoring applications, we will adopt two different datasets obtained from real world deployments with WSNs: the *Intel* and the *Sensorscope* datasets. To represent the tracking applications, we will use the *Ball* dataset, which was synthetically created based on a model of projectile launching, and the *Running* dataset, which was collected using a GPS monitor carried by a person while running through a city.

#### A. *Intel data*

The first dataset was extracted from the experiments described in [15] and encompasses the temperature, relative humidity and luminance collected by sensor nodes inside an office during consecutive days. The whole dataset contains around 2.3 million readings done during 37 consecutive days by 54 sensor nodes that transmitted their measurements every 30 seconds and has been broadly used in several works in the field [9], [16], [17], [18], [19].

In this work, only the temperature values will be used. We selected five consecutive days and observed the data collected by three nodes to illustrate the performance of the predictions. Two nodes were selected according to the variance in their temperature measurements, i.e., those with the lowest and the greatest variance, and the third one was randomly picked (respectively, sensor nodes 35, 21 and 40). The missing values were linearly interpolated and summed to a small white noise. In Figure 1a, we can observe the data collected by the sensors vary between 15°C and 37°C. Even though the measurements do not look very similar, it is possible to see that there is a daily pattern in which their values and variances increase during the day and are more stable and similar at the beginning and at the end of the days.

#### B. *Sensorscope data*

The Sensorscope data was collected by wireless sensor nodes in a deployment made on a rock glacier in Switzerland [20]. The WSN was composed by 10 sensor nodes specially designed for environment monitoring. The experiment lasted 5 days and each sensor node reported its measurements every 2 minutes, which resulted in over 3000 reports per node, each of them

including 8 different measurement types: temperature, solar radiation, relative humidity, soil moisture, watermark, rain level, wind speed and wind direction.

We used the temperature values of three nodes to illustrate the performance of the predictions. The nodes selected were the ones that presented the lowest and the greatest variance in their measurements, and last one was randomly chosen (respectively, sensor nodes 5, 7 and 15), similar to how we selected the nodes in the *Intel* dataset. Again, the missing values were linearly interpolated and summed to a small white noise. Figure 1b shows that, compared with the temperatures observed in the *Intel* dataset, the values are much lower (between  $-12^{\circ}\text{C}$  and  $12^{\circ}\text{C}$ ), which is explained by the sensors' localization and the nature of the experiments. Moreover, there are less abrupt changes, although the presence of the sun clearly changes the values and increases their variance during the days.

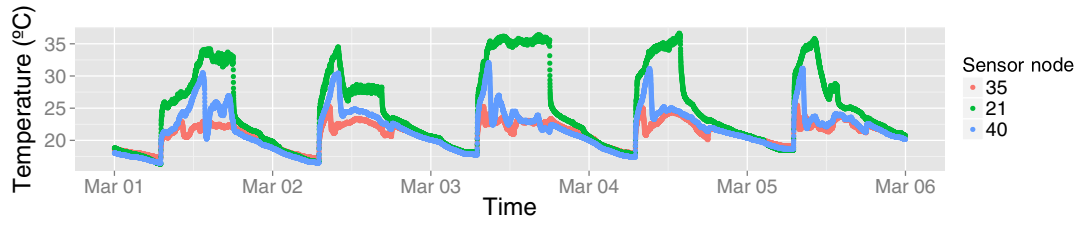
### C. Ball movement

The first dataset used to represent tracking applications was synthetically created in order to simulate an object bouncing on the floor a few times. The data is intended to simulate an object being tracked and can be thought as the vertical position of a ball that hits the floor after being dropped from a certain height. The data points were calculated using the formula of a pendulum with exponential decay [21]:

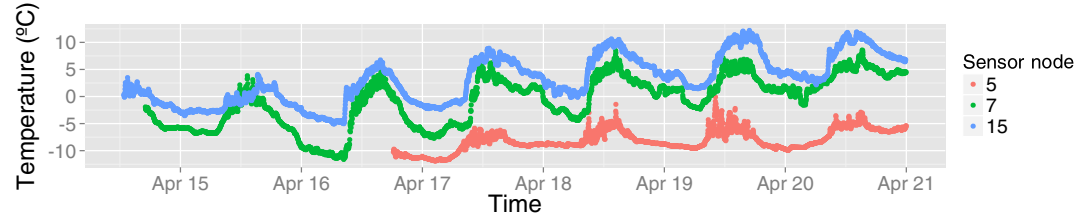
$$\theta(t) = \theta_0 \frac{|\cos(2\pi\lambda t)|}{e^{\gamma t}} + \varepsilon_t, \quad (1)$$

where  $\theta_0$  is the initial amplitude,  $\lambda$  is the frequency,  $\gamma$  represents the decay and  $\varepsilon_t$  is an additive zero-mean, unit variance Gaussian white noise. In order to reproduce different types of movements, we generated three sequences of data, each one with 2800 data points.

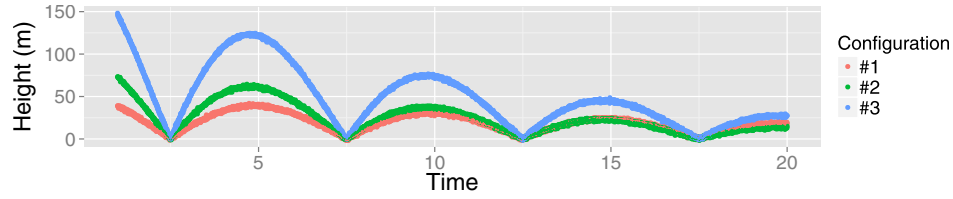
Figure 1c shows the values in the *Ball* dataset set with frequency  $\lambda = 0.1$  hertz and sampled once every second. The first set of points is based on a movement with initial amplitude  $\theta_0 = 50$  meters and decay  $\gamma = 0.05$ . The second set of points has greater initial amplitude and decay ( $\theta_0 = 100$  meters,  $\gamma = 0.1$ ), which means that the object moves faster, resulting on sparser data that may be less predictable. Finally, the third set of points illustrates the fastest object, which has a decay  $\gamma = 0.1$  and the initial amplitude is 200 meters, which means that the changes are more abrupt and less predictable than in the others. Besides these differences, their periodicity can be clearly noticed in the plot.



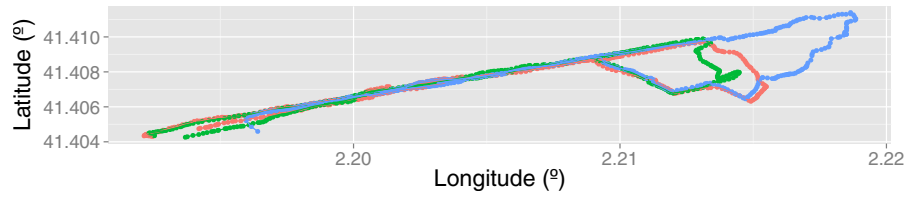
(a) *Intel*: Temperature measured by three sensors in an office [15].



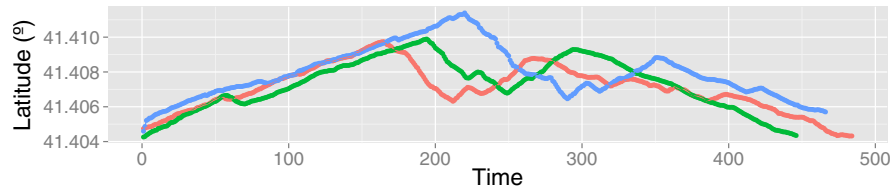
(b) *Sensorscope*: Temperature measured by three sensors in a mountain [20].



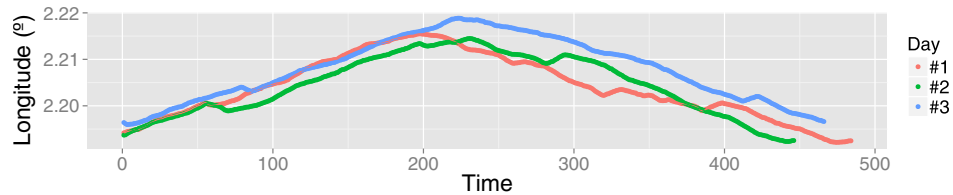
(c) *Ball*: Synthetic data created to imitate bouncing objects.



(d) *Running*: GPS coordinates of a person during street runs.



(e) *Running (latitude)*: Geographic latitude of a person.



(f) *Running (longitude)*: Geographic longitude of a person.

Fig. 1: Datasets used to illustrate the different applications.

#### D. Street runner

This dataset consists on the position of a person while running across the city of Barcelona. The data was collected by a GPS device taken by a person in three different days and each observation was registered in an interval between 1 and 5 seconds after the last one, summing up to 480 data points. Even though the trajectories are similar, the measurements contain noise and variations that are expected to be encountered in other applications for object tracking.

In Figure 1d, the *Running* dataset is shown. The different trajectories among the days are illustrated and it is possible to observe their internal similarity and the absence of periodicity. As we can observe in Figure 1e, changes in the latitude are more abrupt and do not follow any pattern. On the other hand, Figure 1f shows that the longitude varies almost linearly in time and is more intuitive than the changes in the latitude.

### III. FORECASTING METHODS - BACKGROUND

The term *prediction* can either refer to the process of inferring missing values in a dataset based on statistics or empirical probability, or to the estimation of future values based on the historical data. The latter mechanism is also called *forecast* and it is the class of predictions we will refer to in this work. In summary, a forecast is a specific type of prediction in which the predicted values will be observed only in the future. A forecast differs from the other predictions because, when estimating the future, a wider range of possible values must be considered, given the uncertainty about the factors that may impact the scenario under consideration. In order to make it clear to the reader, in this Section we clarify a set of terms that will be often used in this work.

#### A. Time series

A time series ( $X$ ) is a sequence of data points, typically consisting of observations made over a time interval and ordered in time [22]. Each observation is usually represented as  $x_t$ , where the observed value  $x$  is indexed by the time  $t$  at which it was made.

#### B. Information criteria

Information criteria are measures used to estimate the information loss if the time series is modeled by a set of parameters  $\theta$ . The estimated information loss is applied to infer the relative



quality of the parameters and choose the best option given a set of candidates. Assuming that the future data will have the same characteristics as the observations already made, the set of chosen parameters minimizes the information loss, which tends to improve the accuracy of the forecasts. In some cases, the number of parameters is also taken into account, i.e., using less parameters may be considered an advantage, because it avoids overfitting the training data.

Examples of information criterion measures are the Akaike Information Criterion (AIC); the Bayesian Information Criterion (BIC); and the AIC with a correction for finite sample sizes (AICc) [23]. In our experiments, we adopted the AICc as the information criterion to select the most proper set of parameters.

### C. Forecasting method

A forecasting method ( $F$ ) is a function that produces forecasts based on two input values: a time series ( $X$ ) and a set of parameters ( $\theta$ ). The values of  $\theta$  are usually chosen based on the evaluation provided by an information criterion measure, given  $X$ .

### D. Forecasting model

A forecasting model ( $f$ ) is an instance of a forecasting method  $F$ , such that  $f_\theta(X) = F(X, \theta)$ . Every forecasting model is deterministic: its output depend only on the set of observed values. Forecasting models (also called *time series prediction models* [24], [25]) use time series as input to predict future values, which are represented as a function of the past observations and their respective time, i.e.,  $(\hat{x}_{t+1} \dots \hat{x}_{t+i}) = f_\theta(x_t, \dots, x_{t-k})$ , where  $\hat{x}_{t+1} \dots \hat{x}_{t+i}$  are the forecasts for the period between  $t + 1$  and  $t + i$ .

### E. Accuracy

Accuracy measures are used to evaluate the quality of the predicted values based on the difference between the predicted value and the observed value, i.e., the error  $e_t = x_t - \hat{x}_t$  [26]. When necessary, the Mean Absolute Percentage Error (MAPE) will be used to compare the errors of different data types, because it is not scale-dependent.

#### IV. IMPORTANCE OF FORECASTING

In order to illustrate the potential growth in the number of transmissions, we will adopt the ring model for sensor network topologies presented in [32] and extended in [11]. The ring model is based on the average number of neighbors ( $C$ ) of a sensor node and on the number of hops from the GW to the furthest nodes ( $D$ ), as illustrated in Figure 2. By definition, any transmission initiated by a sensor node in ring  $d$  will generate, at least,  $d - 1$  more transmissions to reach the GW, resulting in, at least,  $d$  transmissions in total. Therefore, assuming that the sensor nodes are uniformly distributed in the plane and that there are  $C + 1$  nodes in the unit disk, the first ring will contain  $C$  nodes, and subsequently the number of nodes  $N_d$  in ring  $d$  can be calculated based on the surface area of the annulus<sup>1</sup>:

$$N_d = \begin{cases} 0, & \text{if } d = 0 \\ Cd^2 - C(d - 1)^2 = C(2d - 1), & \text{otherwise.} \end{cases} \quad (2)$$

Hence, adding a new ring to a network with  $D - 1$  rings and density  $C$  represents  $C(2D - 1)$  new sensor nodes in a total of  $CD^2$  nodes.

Recall that a transmission made by a sensor node in ring  $d$  triggers other transmissions in the network, which sums up to, at least,  $d$  new transmissions. Considering that the sensors are programmed to transmit uniformly once every unit of time, all the sensors in the new ring  $d$  together will trigger  $Cd(2d - 1)$  new transmissions. Summing this expression from  $d = 0$  to  $d = D$  gives us that the total number of transmissions in the sensor network during a unit of time is

$$\sum_{d=0}^D Cd(2d - 1) = \frac{2}{3} CD^3 - \frac{1}{2} CD^2, \quad (3)$$

which finally shows that, considering a linear growth in the number of rings, the number of sensor nodes grows quadratically while the number of transmissions grows cubically.

In conclusion, the number of transmissions impacts directly the efficient use of spectrum resources, which (besides the energy consumption of the sensor nodes) is still one of the key challenges that affects the next generation of wireless networks, for instance, WLANs, 4G and 5G networks, as well as traditional multihop WSNs [4].

<sup>1</sup>The region bounded by two concentric circles.

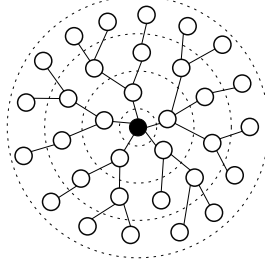


Fig. 2: Sensor network model based on the density of sensor nodes ( $C$ ) and their coverage. The dark circle represents the GW in a network with 3 rings ( $D = 3$ ,  $C = 5$ ).

Forecasting sensed data is a potential candidate to shorten such an increase in the number of transmissions, which is reinforced by its presence in real world sensor network applications. That is, most of the sensor networks forecast missing data, even though it is not explicitly addressed as an issue. It happens, for example, when a sensor measurement cannot be sampled on demand and the value returned by the system to an ordinary query is the latest one (or a combination of some of them), which has been reported by the sensor nodes some seconds (or minutes) earlier. In other words, it is the same technique used by the *Constant* method: the system simply assumes that there was no change in the environment after the last observation [26]. This behavior in turn is exploited by the sensors that avoid unnecessary transmissions and transmit only when a measurement differs by more than a fixed tolerance threshold.

The motivation for exploring advanced forecasting methods to diminish the number of transmissions is detailed in our previous work [11]: based on the ring model, accurate predictions can reduce the amount of transmissions by around 30% in the average case and up to 85% in exceptional cases. The backbone of the model consists of an application of the central limit theorem and the law of large numbers, but no forecasting method was tested to observe whether the ideal accuracy could be achieved. Therefore, having clarified that the use of predictions can benefit the sensor networks, we point out the unanswered question: “Is it feasible to forecast the sensors’ measurements in the sensors?” Discarding the access to other data sources that could improve the forecasts accuracy, the list of forecasting methods is reduced and the results are occasionally worsened by the sensor nodes’ constrained hardware.

For the next generation of sensor applications, a detailed study is necessary to show how accurate can be the forecasts made by the sensors and their respective cost-benefit analysis. In

the following, we will study the feasibility of using complex forecasting methods in the sensor nodes in order to reduce the number of transmissions without reducing the quality of their measurements. Before that, in the next Section, we show how the recent works have adopted forecasting methods to reduce the data transmitted by their sensor nodes and how their operation could be improved.

## V. RELATED WORK

Forecasting methods have been adopted as part of data reduction techniques for sensor networks. In the beginning, the *Constant* method was adopted in several mechanisms, because it corresponds to the constrained energy and power resources of the sensor nodes. That is, the main goal of the first applications was to reduce the number of transmissions without making any complex computation in the sensor nodes [33], [34], [35]

With the evolution of the sensor nodes, their energy and power constraints became less deterrent to the shift of some computation from the GW. As a consequence, several authors started to adopt and test enhanced methods to make more accurate predictions in the sensors. For instance, the AutoRegressive Integrated Moving Average (ARIMA) is the forecasting method adopted in [10]. In that work, the GW is responsible for generating the forecasting models before transmitting the parameter values to the sensor nodes. After receiving the parameters, the sensor nodes are able to compute the same predictions as the GW and locally check their accuracy. Finally, they only transmit the measurements if the forecast was inaccurate. Similarly, the mechanisms presented in [7], [8], [9] use the traditional ARIMA as the method for predicting future measurements. In [9], the authors recognized the limitations of the traditional forecasting methods and suggested the adoption of an Artificial Neural Network (ANN) model when the predictions using ARIMA fail, which in turn requires more computational resources from the sensor nodes.

More recently, the mechanism presented in [37] computes the forecasting models in the sensor nodes before transmitting them to the GW. That is, the sensor nodes became completely autonomous and independent of the data computation made in the GW. On the other hand, the choice of the method is still restricted by the sensor nodes' memory and processing power limitations, which also narrows the range of situations in which it can be successfully adopted.

Following the approaches of shifting the data computing to the sensor nodes, in [38], a real

WSN was deployed and part of its energy was saved through the reduction in the number of transmissions using different prediction methods: *Constant*, weighted moving average, ARIMA and Exponential Smoothing (ES). The experimental results showed that the *Constant* method was the best option in the use case considered by the authors, due to its better accuracy and the higher energy consumption of the others. Even though there is a clear contribution towards the (non-)adoption of complex forecasting methods in sensor networks, the results are specific to the application presented by the authors and different use cases cannot be inferred from their study.

After observing the evolution of the sensor networks and the adoption of more complex prediction methods in the field, we noticed that there was a need to develop a broad study about the prediction algorithms from a statistical point of view that could serve as a reference for future developments in the integration of data prediction methods into sensor networks. Comparisons between the state-of-the-art algorithms have been also shown in the M3's competition results [39] and, although they show that the forecasts perform well in several cases, they do not consider the limited data access and processing power inherent to the sensor nodes. In the next Section, we use sensor network data to present a comparison between the forecasting methods presented before under the constrained sensor nodes' perspective.

## VI. EXPERIMENTAL RESULTS

The first step to validate the feasibility of using forecasting methods was to systematically apply the different methods over splits of the data collected by real sensors in different experiments. Each split is defined by a *history* plus a *window*: the former represents the measurements made in the past and the latter the measurements to be forecast. The idea of observing different *history* and *window* lengths is to synthesize the evolution of the sensor nodes' memory and computational capacities. Hence, the experimental results illustrate the comparison between different configurations and how the sensor nodes' evolution impact the forecasts accuracy.

### A. Parameter study

From now, we define as a *scenario* each combination of *history* and *window* lengths observed in a *dataset*. In the experiments, for example, a scenario with history length of 100 and window length equal to 10 in the *Ball* dataset has been represented by 200 splits of data randomly picked

from that dataset. Before testing each scenario under different forecasting methods, we detail their characteristics in the following.

1) *Datasets*: The tests were made using all the datasets presented in Section II: *Intel*, *Sensorscope*, *Ball* and *Running*. Each dataset is composed by 3 *groups* of data, i.e., *Intel* and *Sensorscope* have 3 different sensors each, *Ball* was constructed using 3 different parameter configurations and *Running* contains data from 3 different days, which was separated along two dimensions (latitude and longitude), and considered as two different sets of data. The forecasts were made based on 200 splits of data randomly picked from each group. This setup represents the data heterogeneity expected in different sensor networks.

2) *Forecasting methods*: In our experiments, we tested the forecasting methods that are broadly used in data applications, thanks to their scalability and reliability: the *Constant*, the *Linear*, the Simple Mean (SM), the Exponential Smoothing (ES), the AutoRegressive Integrated Moving Average (ARIMA) and the Artificial Neural Networks (ANNs) methods. All of them are explained in detail in [26].

Different from the others, the ANNs are soft computing solutions that cannot be bounded by a computational time limit [28], [29]. Therefore, besides it, all the computing complexities are summarized in Table I. Usually, the complexities are given in function of the number of values used to generate a forecasting model ( $h$ ) and the number of values that will be forecast ( $w$ ). In some cases, other specific method parameters ( $p$ ,  $q$  and  $k$ ) also impact the algorithms' complexity. In short, their values can vary, but usually  $p \in [0, 2]$ ,  $q \in [0, 2]$  and  $k \in [0, 10]$ .

3) *History*: The *history* is the set of data points used during the learning phase and its length impacts the preprocessing time complexity, i.e., the computing time required to find the best prediction model or to set up the model parameters. Thus, the simplest methods, such as the *Constant* and the *Linear*, are not affected by the history length, but the time spent to set up an ARIMA model increases quadratically according to the history length and must be considered before its adoption in the simplest sensor nodes. We considered cases in which the history length varied among 5, 10, 20, 50, 100, 200, 500 and 1000.

4) *Window*: The *window* is the set of values that must be forecast and represent future measurements. Hence, they are not considered at the moment in which the forecasts are produced, but only to measure their accuracy. We experimented scenarios where 1, 5, 10, 20, 50, 100, 200, 500 and 1000 values were predicted at a time. The window length might affect the runtime,

| Method                     | Preprocessing time complexity | Runtime complexity       | Space complexity              |
|----------------------------|-------------------------------|--------------------------|-------------------------------|
| Constant                   | $\mathcal{O}(1)$              | $\mathcal{O}(1)$         | $\mathcal{O}(1)$              |
| Linear                     | $\mathcal{O}(1)$              | $\mathcal{O}(w)$         | $\mathcal{O}(1)$              |
| Simple Mean (SM)           | $\mathcal{O}(h)$              | $\mathcal{O}(1)$         | $\mathcal{O}(1)$              |
| Exponential Smoothing (ES) | $\mathcal{O}(k^3 h)$          | $\mathcal{O}(w)$         | $\mathcal{O}(1)$              |
| ARIMA( $p, d, q$ )         | $\mathcal{O}(k^3 h^2)$        | $\mathcal{O}((p + q) w)$ | $\mathcal{O}(\max(p, q + 1))$ |

TABLE I: List of forecasting methods and their complexities

which can be either constant or increase linearly, as shown in Table I.

### B. Constant predictions

As explained before, the conventional assumption that the measured values did not change on the absence of data is nothing else than an application of the *Constant* method. In other words, the *Constant* method is widely (and inadvertently) adopted in sensor networks due to the low bandwidth links and the occasional low computational capabilities of the sensor networks, because it is not necessary to set up any model nor calculate parameters in order to assume that the measured value is simply the same as the last one received. Given its practicality and low complexity, this is the most common method adopted in sensor networks, became the default method and has been rarely challenged in recent works. The common sense, however, does not measure its limitations, weaknesses or the restrictions of such an option. For example, we observed that in 46.05% of the cases (i.e., in 35 out of 76 scenarios), other prediction models showed a statistically significant positive difference (with 95% confidence intervals) when compared with the *Constant*. Therefore, we decided to adopt the *Constant* method as a baseline and explicitly compare its results with the other methods later.

As shown in Table II, the MAPEs of the *Constant* predictions vary according to the data set. The MAPE is calculated as  $\frac{1}{n} \sum_{t=1}^n |100e_t/x_t|$ ; hence smaller values represent more accurate forecasts. As an example, the forecast of 1 value has very low relative error in the *Intel* dataset (0.00965%), and it is near 1% when the window reaches its maximum value, i.e., around 1000 times larger. On the other hand, the *Ball* dataset presents larger MAPE when there is only one value to forecast (19.9%), but it increases slower when the window increases, e.g., it is “only”

|                           | Window length |         |         |         |         |         |         |         |         |
|---------------------------|---------------|---------|---------|---------|---------|---------|---------|---------|---------|
| Data set                  | 1             | 5       | 10      | 20      | 50      | 100     | 200     | 500     | 1000    |
| <i>Intel</i>              | 0.00965       | 0.02156 | 0.03305 | 0.05487 | 0.11318 | 0.19524 | 0.34679 | 0.6504  | 1.03378 |
| <i>Sensorscope</i>        | 0.05932       | 0.11075 | 0.14691 | 0.20212 | 0.32285 | 0.50029 | 0.81077 | 1.27596 | 1.15538 |
| <i>Ball</i>               | 19.869        | 24.264  | 26.533  | 34.71   | 56.734  | 82.559  | 149.126 | 264.354 | 347.395 |
| <i>Running(latitude)</i>  | 0.00015       | 0.00042 | 0.00071 | 0.00117 | 0.00237 | 0.00311 | 0.00359 | —       | —       |
| <i>Running(longitude)</i> | 0.00404       | 0.01196 | 0.02166 | 0.04057 | 0.09318 | 0.17626 | 0.37002 | —       | —       |

TABLE II: Accuracy (MAPE) of the *Constant* predictions.

17.5 times larger (347.395%) in the scenario with 1000 values.

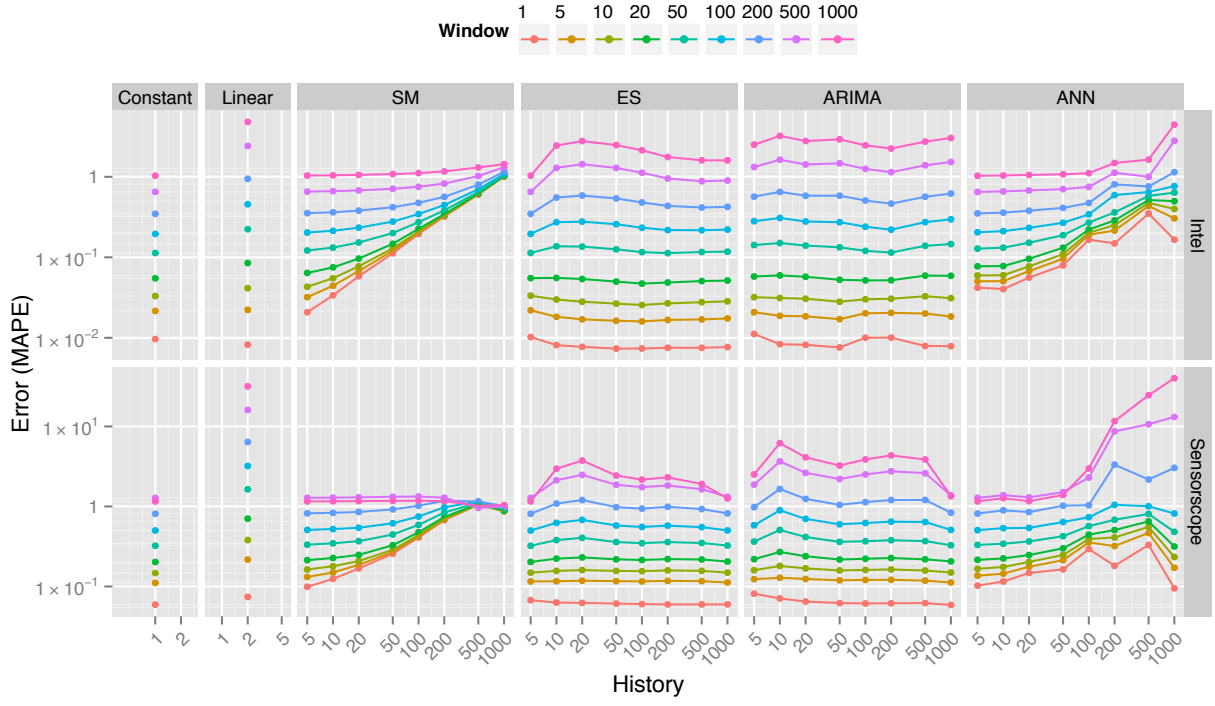
Regardless of the network types and the data sources, the explanation for such variances lies in the composition of the data. Our results corroborate the initial intuition after observing the data from the datasets in Figure 1: the *Constant* method fails more often in the *Ball* than in the other scenarios, since the former has sharper curves where the values rapidly increase and decrease often.

### C. Constant predictions vs. Linear and Simple Mean

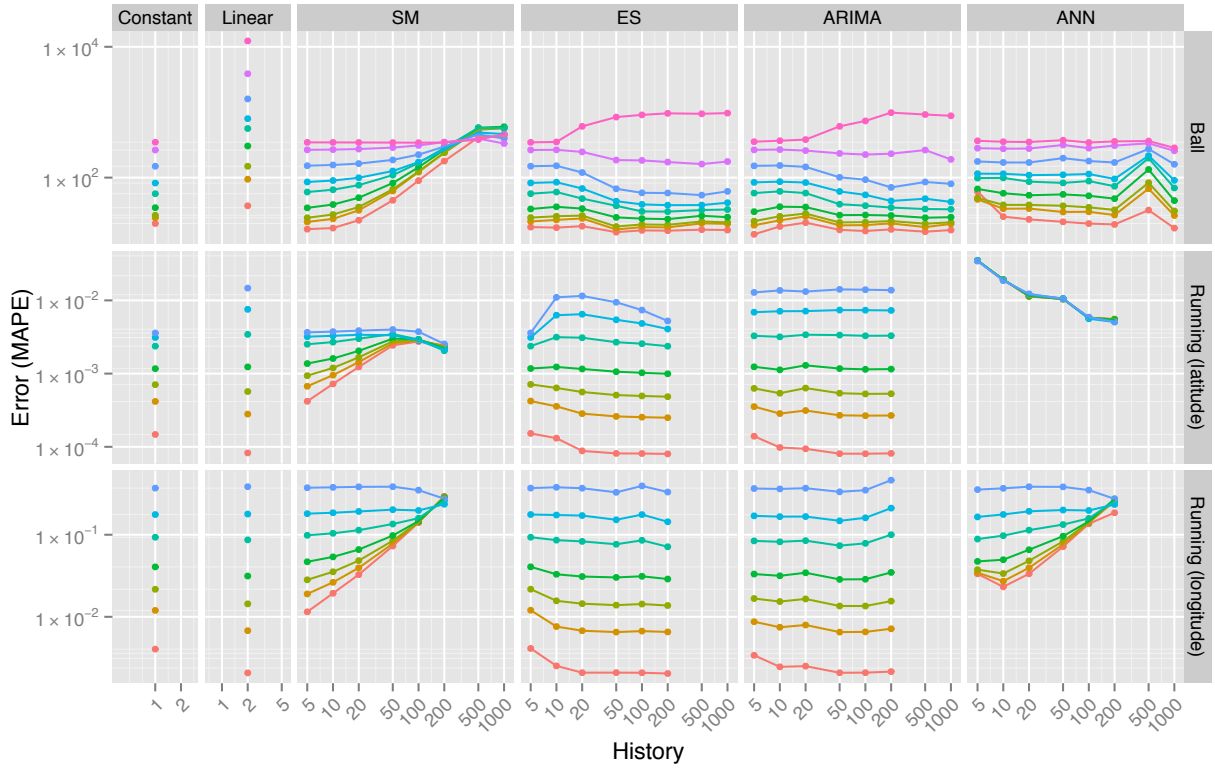
As the *Constant* method uses only the last value and the *Linear* method uses only the last two values to forecast, we did not include the complete history lengths in Figure 3. In general, the *Constant* method was more accurate than the *Linear* method. The greatest difference between them was observed in the *Ball* dataset, when the MAPE is more than one order of magnitude greater after adopting the *Linear* method, due to the noisy values. The exceptions were in the *Intel* dataset when the window had length equal to 1 and in the *Running* dataset when the window length was small (between 1 and 10). More specifically, there is only one statistically significant improvement (with 95% confidence intervals) when the *Linear* method is adopted in the *Running* (latitude) dataset when the window length is equal to 1. In this case, the MAPE is  $8.255 \cdot 10^{-5}$  while it is  $14.74 \cdot 10^{-5}$  when the *Constant* method was adopted.

The SM method mainly forecasts as accurately as the *Constant* in the *Ball* dataset with small history length (between 5 and 20), when the data usually has the stationarity property. In fact, the SM was the best option only in 7.33% of the scenarios and the greatest improvement was in the *Running* (latitude) dataset with history length equal to 200 and window length equal to 100,





(a) Accuracy in the monitoring applications.



(b) Accuracy in the tracking applications.

Fig. 3: Comparison between the *Constant* and the methods that forecast in polynomial time.

where the SM method could reduce by 31.46% the error generated by the *Constant* method. In most of the cases, the SM accuracy decreases noticeably when the history length is increased, because the data is neither stationary nor normally distributed. On a side note, sensed data is rarely stationary or normally distributed, which exposes the limitation of this method for general use cases.

#### D. *Constant predictions vs. Exponential Smoothing vs. ARIMA*

In comparison with the ES, the *Constant* method forecasts less accurately when the window is smaller, i.e., the window length is between 1 and 10 (in exceptional cases, 20). Moreover, we did not observe significant improvements in the accuracy of the ES method when the history grew larger than 50, i.e., there was no advantage in using 100 or 200 values instead of only the last 50.

In comparison with the ARIMA, the *Constant* method was significantly outperformed most of the times when the window length has been set to 1 or 5. The only exceptions were when the history length was 100 or 200, even though the accuracy was very similar (less than 0.0004% of relative difference). In addition, the ARIMA method had better accuracy when the history was at least 10 times longer than the window. For instance, when the history was at least 10 times larger than the window, the average MAPE was 0.395%; and 1.732% otherwise.

There were only few specific cases when the ES and the ARIMA models clearly outperformed the *Constant* method, i.e., there was a statistically significant difference between their results with 95% confidence intervals: in the *Ball* dataset, when 50 and 100 observations were used to predict the next 20 measurements; and in the *Running* (longitude) dataset, when the next 20 values were forecast. Considering the different datasets, the *Constant* method was always the best option in the *Sensorscope* and in 4 out of 20 scenarios of the *Intel* data, which can be explained by the nature of the data, i.e., in such cases the sensors were programmed to transmit every time interval, regardless the changes in their measurements, resulting on several consecutive similar measurements. On the other hand, the forecasts accuracy over the *Ball* data were improved in all the scenarios in which we used more than 10 measurements and predicted less than 120 values (i.e., 60% of the cases). Furthermore, in the *Running* datasets, it was always possible to find models that forecast more accurately than the *Constant* method.

As a counterpoint to the improvements explained above, both ES and ARIMA had lower

accuracy when the window was larger than 100 (either 500 or 1000), except in the *Ball* database, in which they still provided accurate forecasts when the window length was 500. In conclusion, none of these methods always outperformed the others, but ES and ARIMA were regularly more accurate than the *Constant* for small window lengths (i.e., 1, 5 and 10), regardless of the scenario and the application.

#### E. *Constant predictions vs. Artificial Neural Networks*

As explained before, ANNs are soft computing solutions and have no upper limit time to compute their forecasts. The lack of guarantee in terms of time required to converge into a final model can be also observed in the accuracy, as shown in Figure 3. In general, there are few cases in which the ANN is more accurate than the *Constant*, and most of them happen when the history has at least 100 values, such as in the *Ball* dataset with window 1, 500 and 1000 and history 1000. Additionally, in the *Running* (longitude) dataset, *Constant* is outperformed when the window has length 200.

Overall, we notice that there is a large difference in the results between the monitoring and the tracking applications. In the latter case, there is a clear decreasing trend in the errors when a longer history is adopted. Because the tracking data is always changing and providing new information to the model, the ANN requires less values to capture their trends in the short term. However, even in the largest history length analyzed (2000 values), the ANNs did never provide predictions more accurate than the *Constant* method, independently of the scenario under consideration.

## VII. EFFECTIVENESS OF THE FORECASTS

One contribution of this work is a study that considers the data heterogeneity inherent to the sensor networks, which is illustrated by the datasets encompassing different data types and originated in different scenarios. However, the differences between sensor networks are not only in the data values, but also in their requirements. For example, a sensor network that is measuring the temperature in a data center might require higher precision than one placed in the mountains, because the indoor temperature may be used to control an air conditioning system that avoids damages from excessive heat. Hence, the comparison between the MAPEs is not enough to translate how useful and effective is the use of forecasting methods in sensor networks. In other

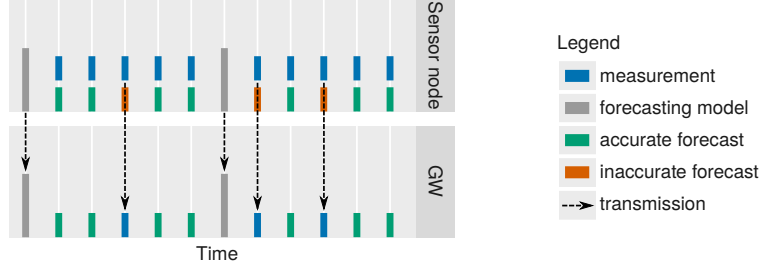


Fig. 4: In a dual prediction scheme, sensor nodes transmit new forecasting models every time interval. A measurement is transmitted only if its forecast is inaccurate.

words, the MAPEs illustrate the numerical differences in the forecasts accuracy of the methods observed, but they do not provide the practical benefit that they would represent in a real scenario.

Therefore, in this Section, we evaluate the effectiveness of the forecasts and conclude which algorithms actually benefit the sensor networks. We assume a dual prediction scheme [37] illustrated in Figure 4. In this scheme, a sensor node has two tasks: (i) make measurements; and (ii) fit a forecasting model, based on a set of measurements made beforehand. Once the minimum number of measurements is collected, the sensor node is able to fit a forecasting model and transmit it to the GW. Using the same forecasting model, the GW is able to forecast the next measurements locally without having to receive them from the sensor node. From this point, the sensor node will only transmit a measurement if its forecast is inaccurate, i.e., the forecast differs by more than a fixed threshold from the current measurement.

Our conclusions will be based on the estimated number of transmissions that could be saved in each case, which represents a cost-benefit relationship of adopting a forecasting method. To make such an evaluation, we estimate how many transmissions could be avoided if the *Constant* was used and compare it with the ES and the ARIMA methods, which were the only methods that could forecast as accurate as the former one in our previous observations.

#### A. Acceptance threshold

In order to define whether a transmission could be avoided, it is necessary to annotate, firstly, which values are relevant in a scenario. In general, if the absolute difference between the current measurement and the last one transmitted is smaller than a certain  $\Delta_{\min}$  (the *acceptance threshold*), the current measurement does not provide valuable information to the network and

| Data set           | Group 1 | Group 2 | Group 3 |
|--------------------|---------|---------|---------|
| <i>Intel</i>       | 58.13%  | 46.36%  | 60.14%  |
| <i>Sensorscope</i> | 61.36%  | 33.02%  | 33.78%  |

TABLE III: Percentage of absolute differences between consecutive measurements that are below the *acceptance threshold* in the dataset groups used in the experiments.

its transmission might be avoided. Using the *acceptance threshold*, it is possible to infer the potential reduction in the number of transmissions if we consider that a prediction is accurate whenever the absolute difference from the real value is smaller than  $\Delta_{\min}$ .

### B. Results without quality loss

As described before, one of the goals of our study is to observe whether it is possible to reduce the number of transmissions using forecasting methods without reducing the quality of the measurements. To simulate that, we will adopt the smallest values possible for the  $\Delta_{\min}$ : the sensors' resolution used in each experiment. A sensor's resolution is the smallest measurement that can be indicated reliably, e.g., if a temperature sensor's resolution is  $0.01^{\circ}\text{C}$ , it cannot precisely measure the difference between  $20.001^{\circ}\text{C}$  and  $20.007^{\circ}\text{C}$ . In this case, we could assume that any change smaller than  $0.01^{\circ}\text{C}$  in the temperature is never relevant; and hence if a forecast differs by less than  $0.01^{\circ}\text{C}$  from the real observation it is accurate and will not trigger a transmission from the sensor node to the GW. The following values of  $\Delta_{\min}$  were considered in each dataset:

- **Intel dataset:**  $0.01^{\circ}\text{C}$ . Since the Mica2Dot's specification does not include the temperature sensor's resolution [?], we defined the  $\Delta_{\min}$  as the minimum difference between any pair of measurements observed in the data. On a side note, we highlight that it is the same resolution of Sensirion SHT11, a temperature sensor broadly used in several wireless sensor nodes similar to Mica2Dot [?].
- **Sensorscope dataset:**  $0.045^{\circ}\text{C}$ . According to the TinyNode's specification [?], it uses an analog temperature sensor (LM20) that can measure from  $-55^{\circ}\text{C}$  to  $130^{\circ}\text{C}$  and the microcontroller has a 12-bit analog-to-digital converter. Therefore, we calculated the sensor's resolution as  $(130 - (-55))/2^{12}^{\circ}\text{C}$ .

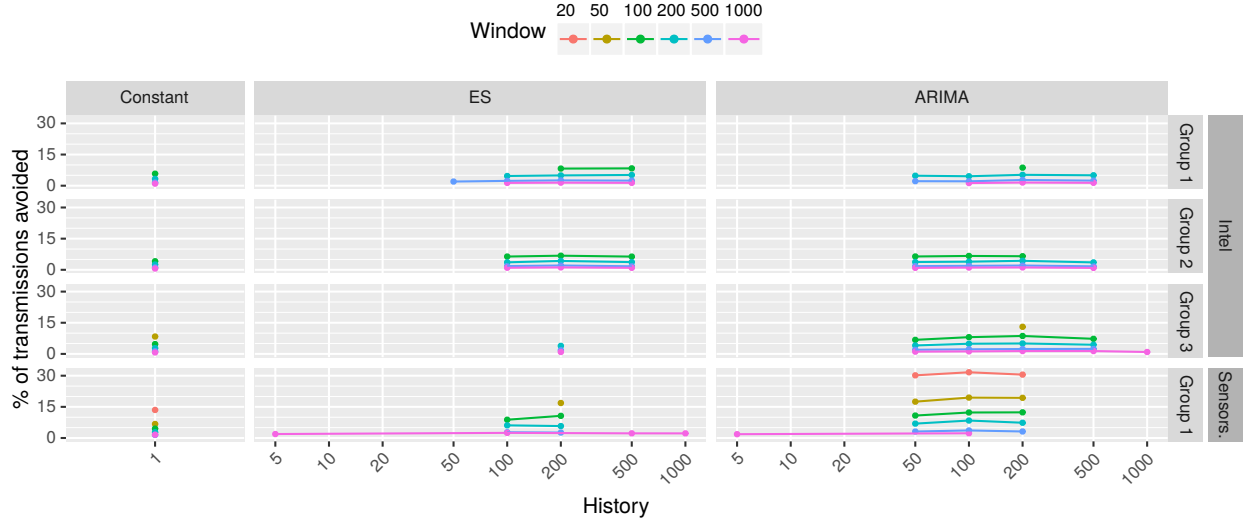


Fig. 5: The percentage of transmissions that could be avoided using each forecasting method. We included only the cases in which ES and ARIMA could save at least 2 transmissions more than the *Constant* method.

- **Ball dataset:** 0.001 meter. As a reference, we adopted the specification of the AR3000 sensor, a long range laser sensor that can accurately measure distances of up to 300 meters [?].
- **Running datasets:**  $8.38 \cdot 10^{-8}$  degree. Since the sensor's specification is not publicly available, we defined the  $\Delta_{\min}$  as the minimum difference between any pair of measurements observed in the data. This value represents nearly 1 centimeter of distance along the latitude direction and around 0.7 centimeters along the longitude orientation [?].

We highlight that only the *Intel* and the *Sensorscope* datasets had consecutive values such that their absolute difference is smaller than the *acceptance threshold*, due to the consecutive similar values and the missing values filled beforehand. Table III shows the percentage of absolute differences between consecutive measurements that are below the *acceptance threshold*.

Differently from the *Constant* method, ES and ARIMA are based on models and use sets of parameters to forecast new values. In a real sensor network where the forecasting model is generated in the sensor nodes, it means that the same parameters must be shared with the GW. That is, the parameters must be transmitted; and this can either be done by triggering a

new transmission or simply by attaching them to a measurement transmission. Hence, using ES or ARIMA with window length equal to 1 cannot reduce the number of transmissions in the sensor nodes, given that the model would have to be updated after each measurement. In fact, updating the model after each measurement would eventually increase the energy consumption in the sensor nodes, given that their parameters require an extra computational time inexistent in the *Constant* method.

Furthermore, depending on the scenario, an inaccurate forecast may trigger the transmission of the real measurement to the GW. Then, if the *Constant* method has been adopted, the new measurement can be used to forecast new values, resetting the forecasting window. On the other hand, the ES and the ARIMA methods may trigger (at least) one extra transmission to establish the same forecasting model in the sensor node and in the GW. Given the occasional extra transmission, we make a fair comparison by focusing only on the scenarios in which the ES and the ARIMA methods could reduce at least 2 transmissions more than the *Constant* method.

Finally, considering the window length as the maximum number of measurements that can be transmitted (in case that all forecasts are inaccurate), Figure 5 shows the percentage of transmissions that could be avoided using the *Constant*, ES and ARIMA methods. For this representation, we did not consider any extra transmission that could be occasionally required to transmit the forecasting models' parameters. As explained above, to improve the readability, we included only the cases in which the ES and the ARIMA methods accurately predicted, on average, at least 2 values more than the *Constant* method.

The results show that the *Constant* method is the best option when the window length is smaller than 20. Curiously, as discussed in the previous Section, the *Constant* method was regularly less accurate than the ES and the ARIMA methods when the window length was 1, 5 or 10. This illustrates the importance of analyzing the real effectiveness of the forecasts when applied to real use cases.

Considering all scenarios, the greatest improvement of a forecasting method in comparison with the *Constant* method was observed in *Sensorscope* when the window length was set to 20: the number of transmissions avoided using ARIMA was 18.1% greater than using *Constant* method, i.e., the ARIMA model could accurately forecast nearly 3.9 transmissions more than the *Constant* method. In this scenario, the ARIMA method could be used to avoid an average of 6.33 transmissions every 20 measurements, which represents a reduction of 31.65% in the

number of transmissions.

In terms of history length, we observed that increasing the number of values in the history from 100 to 200 increased the number of avoided transmissions in 70% of the cases illustrated in the plot. In general, ES could reduce more transmissions when the history length was between 100 and 200, while ARIMA also performed well using only 50 values. These results, together with the observations obtained in the previous tests, suggest that both forecasting methods can be more accurate and bring improvements when the history length is increased up to 200 (and not to 500 or 1000).

In conclusion, our experimental results show that it is possible to reduce the number of transmissions using forecasting methods without losing any quality of the measurements provided by the sensors. The effectiveness of such methods, however, may vary from sensor to sensor even if the environment and the phenomena observed is the same, for example, in the *Sensorscope* dataset only the sensor node that sensed the *Group 1* data could have its transmissions reduced. The decision about whether to adopt forecasting methods or not can be made based on the methodology presented in this paper, after observing the sensor nodes' computing capacities and the environment under observation.

Finally, we observed that, as shown in Table III, in the four cases illustrated in the plot, more than 45% of absolute differences between consecutive measurements were below the *acceptance threshold*. Such a coincidence suggests that the forecasting methods can be more effective under some circumstances.

### C. Results with different sensors' resolution

The results illustrated above suggest that if the sensors sampled more often and measured more "similar" values, the ES and the ARIMA methods would be able to reduce more transmissions than the *Constant* method. In order to observe the impact of the similarity between consecutive data samples, we simulated a change in the sensors' resolution in each *Group* to values such that the chances of observing two similar consecutive values was 50%. For example, the sequence of temperature values {20.1°C, 20.1°C, 20.4°C, 20.6°C, 21.5°C, 21.6°C, 21.8°C} measured by a sensor with resolution equal to 0.1°C has only one pair of similar consecutive values (out of 6). However, if the sensor's resolution was 0.5°C, the same sequence would be measured as {20.0°C, 20.0°C, 20.5°C, 20.5°C, 21.5°C, 21.5°C, 22.0°C} where half of the values are the same



| Data set                   | Group 1   | Group 2  | Group 3   |
|----------------------------|---|--|---|
| <i>Intel</i>               | 0.0098°C  | 0.0101953°C  | 0.009653105°C   |
| <i>Sensorscope</i>         | 0.02137582°C  | 0.0840074°C  | 0.07867205°C  |
| <i>Ball</i>                | 0.9410768 meter   | 0.9699227 meter  | 0.9555685 meter   |
| <i>Running (latitude)</i>  | $3.35276 \cdot 10^{-5}$ degree<br>( $\sim 3.72$ meters) | $3.704801 \cdot 10^{-5}$ degree<br>( $\sim 4.11$ meters) | $3.43658 \cdot 10^{-5}$ degree<br>( $\sim 3.81$ meters) |
| <i>Running (longitude)</i> | 0.0001015048 degree<br>( $\sim 8.49$ meters)            | 0.0001128204 degree<br>( $\sim 9.43$ meters)             | 0.0001072884 degree<br>( $\sim 8.97$ meters)            |

TABLE IV: New sensors' resolution and *acceptance thresholds* set in order to have similar consecutive values in 50% of the time.

| Data set                   | Window length | History length | Saved transmissions using the <i>Constant</i> method | Saved transmissions using another forecasting method |
|----------------------------|---------------|----------------|--|--|
| <i>Intel</i>               | 20            | 200            | 8.59%  | 20.91% using ARIMA                                   |
| <i>Sensorscope</i>         | 20            | 100            | 6.87%  | 21.08% using ARIMA                                   |
| <i>Ball</i>                | 50            | 1000           | 14.95%   | 43.03% using ARIMA                                   |
| <i>Running (latitude)</i>  | 50            | 100            | 0.58%  | 5.21% using ES                                       |
| <i>Running (longitude)</i> | 5             | 200            | 13.91%   | 51.74% using ARIMA                                   |

TABLE V: Highest improvements in the percentage of saved transmissions.

as the last one observed. On the one hand it represents a change in the *acceptance threshold*, but on the other hand it is similar to changing the sensors' sampling rate to a value in which the measurements are the same as the last one measured in 50% of the time.

After adjusting the sensors' resolution to the values observed in Table IV, we obtained the desired scenario described above and the results shown in Figure 6. As well as before, to improve the readability, we included only the cases in which the ES and the ARIMA methods accurately predicted, on average, at least 2 values more than then *Constant* method.

We can observe that it is possible to reduce the number of transmissions regardless of the application type, even though each dataset has a different average percentage of avoided transmissions per window length. Table V shows the greatest reductions in the number of transmissions after setting new resolutions for the sensors. In the best case, the ARIMA method can reduce more than 50% of the transmissions in the *Running* (longitude) dataset, which

represents a significant improvement especially taking into consideration its potential to improve the end-to-end throughput and reduce the delays in other tracking applications.

Furthermore, in comparison with the previous results, now it is possible to observe cases in which there is a reduction in the number of transmissions with smaller window lengths (5 and 10). Probably due to the nature of the measurements and an eventual seasonality, when the window length was set to 1000, the ES and the ARIMA methods could reduce the number of transmissions only in the monitoring applications. Again, the great majority of the improvements using ES and ARIMA needed between 50 and 200 values in the history.

## VIII. CONCLUSION

In this work, we provided a broad study about the adoption of forecasting methods in sensor networks. First, we presented the importance of reducing the number of transmissions in sensor networks and assessed the forecasting as a potential candidate to assume such a responsibility. Related works in the field that adopted forecasting methods to reduce the data transmission in the sensor networks corroborated our initial guess and motivated our further experiments. In order to explore the diversity of the sensor network and IoT applications, we based our conclusions on the experimental results over 4 datasets from different types of origins, embracing the data heterogeneity expected from real implementations, such as various data types represented in different units of measurement and collected from different applications. Finally, after observing the relative accuracy and the real efficacy of the different forecasting methods, we concluded that adopting complex forecasting methods in the sensors can be as promising as we initially suspected: using forecasting methods, it is possible to reduce the number of transmissions without reducing the quality of the measurements provided by the sensor networks.

As discussed before, the computing times of ES and ARIMA are respectively proportional to the length and the squared length of the set of values used to generate the forecasting models. Hence, the reduction in the number of transmissions can be especially achieved when the sensor nodes have high computational power to compute complex algorithms, since it was necessary between 50 and 200 values to generate forecasting models that could effectively reduce the number of transmissions. In other words, the simplest wireless sensor nodes, such as the TelosB [1], may not have enough computing power to process these forecasting methods or enough memory to store the necessary values needed to reduce the number of transmissions to

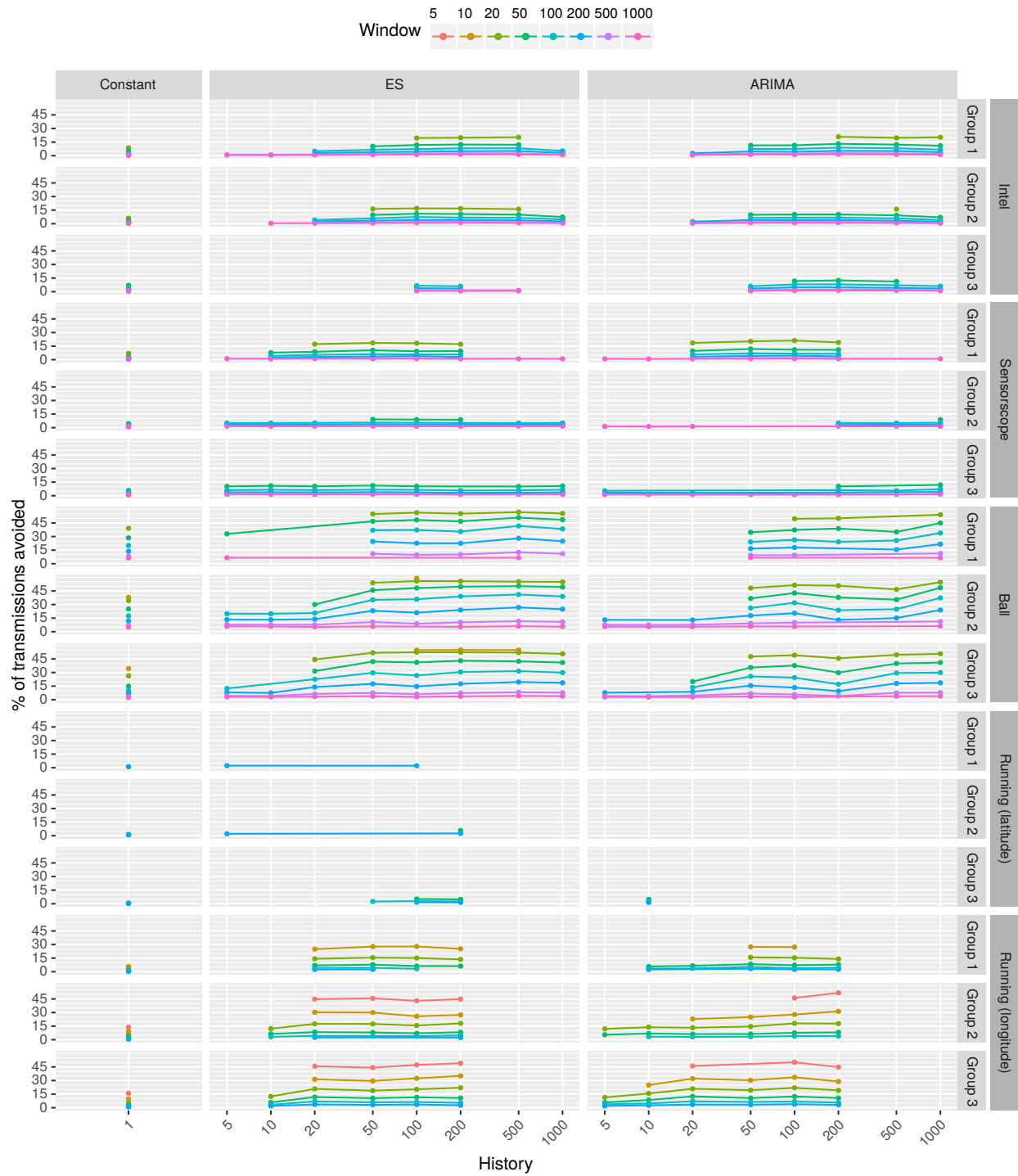


Fig. 6: In cases where the chances of measuring two consecutive values is 50%, it is possible to have a high reduction in the number of transmissions without reducing the quality of the measurements provided by the sensor network.

the GW. We conclude that the evolution of the sensor nodes will make it possible to forecast their data and has potential to support the exponential growth of IoT, regardless of their limited access to information that could be provided by neighboring sensor nodes or external data sources. In other words, the number of transmissions can be reduced by simply exploiting the sensors' proximity to the origin of the data and their computational power without losing the quality of the measurements, because the current state-of-the-art forecasting methods are accurate enough to substitute the real measurements made by the sensors.

#### ACKNOWLEDGMENT

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